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Demand Response Economic Assessment with the Integration of Renewable Energy for Developing Electricity Markets

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Abstract: Electricity disparity in sub-Saharan Africa is a multi-dimensional challenge that has significant implications on the current socio-economic predicament of the region. Strategic implementation of demand response (DR) programs and renewable energy (RE) integration can provide efficient solutions with several benefits such as peak load reduction, grid congestion mitigation, load profile modification, and greenhouse gas emissions reduction. In this research, an incentive and price-based DR programs model using the price elasticity concepts is proposed. Economic analysis of the customer benefit, utility revenue, load factor, and load profile modification are optimally carried out using Freetown (Sierra Leone) peak load demand. The strategic selection index is employed to prioritize relevant DR programs that are techno-economically beneficial for the independent power producers (IPPs) and participating customers. Moreover, optimally designed hybridized grid-connected RE was incorporated using the Genetic Algorithm (GA) to meet the deficit after DR implementation. GA is used to get the optimal solution in terms of the required PV area and the number of BESS to match the net load demand after implementing the DR schemes. The results show credible enhancement in the load profile in terms of peak period reduction as measured using the effective load factor. Moreover, customer benefit and utility revenues are significantly improved using the proposed approach. Furthermore, the inclusion of the hybrid RE supply proves to be an efficient approach to meet the load demand during low peak and valley periods and can also mitigate greenhouse gas emissions.

Keywords: demand response; price elasticity; strategic selection index; renewable energy; load profile

1. Introduction

Access to a sustainable, affordable, and reliable source of energy is key to the socio-economic advancement of Africa. The electricity access rate for sub-Saharan Africa reported as 62.5%, in 2017, with millions remaining connected to unreliable networks that cannot satisfy their electricity needs. A significant portion of this region has electricity access rates estimated at 20%, and two out of three people lack access to modernized energy services [1,2]. The electricity access rate in sub-Saharan Africa improved from 43% in 2016 and it is estimated that it will improve by 59% in 2030. Nonetheless, a

significant amount of the populace is without access to electricity. Of the 674 million people that will be without access to electricity in 2030, 90% are in sub-Saharan Africa [3]. Sub-Saharan Africa is plagued with the problem of deficiency in electricity supply and excessive demand in both grid-connected and off-grid regions; often, consumers are connected to an unreliable grid that does not satisfy their daily energy service needs. Despite being connected, some consumers cannot afford to consume electricity due to high energy bills. Moreover, the levels of service interruption are appalling, with no option but to hinge on diesel generators with a high cost of operation. Meeting the electricity disparities in sub-Saharan Africa is a multi-dimensional challenge with significant implications on how to frame the region's energy predicament.

1.1. Sierra Leone's Energy Sector Situation

Sierra Leone, located on the coast of West Africa, flanked by Liberia, Guinea, and with an estimated population of 7 million, has experienced significant economic growth in recent years. The disastrous outcome of the civil war, crippling effects of dwindling global demand of iron ore and the outbreak of the Ebola epidemic are still present. The energy requirement of the country is immensely under-served, with 20.3% having access to electricity, with the capital city of Freetown accounting for a significant amount of the demand [4,5]. In [6], the authors highlighted the current state-owned installed generation capacity of 130 MW across the country and the projected load demand for the industries, commercial, and residential consumers. Inadequate motivations for investment in large-scale renewable energy technologies is highlighted as a significant obstacle to Sierra Leone's sustainable energy development.

In order to mitigate the immediate power challenges in the capital Freetown and to ensure affordable and sustainable power supply, the government recently renegotiated the electricity tariffs of a 30 MW offshore floating power plant, with an independent power producer (IPP) (karpower) from US\$19.596/kWh to 16.4 US\$/kWh resulting in an estimated US\$9 million annual savings [7]. The electricity sector in Sierra Leone is severely challenged with the problem of low network capacity, coupled with high system losses (commercial and technical) estimated at 35% in the distribution network. Heavy fuel oil thermal generating plants are required to supplement the current generation as a result of seasonal variations in hydropower generation, which often results in an imbalance between generation and load demand. The scale of the imbalance is highly seasonal, being far less in the raining season as the main hydropower provides 40 MW to the capital, Freetown, compared to less than 10 MW in the dry season. The mismatch in generation capacity and load demand has forced grid operators to issue emergency notifications for voluntary conservation response and load shedding, especially in the capital city of Freetown, which, in turn, has resulted in a substantial financial loss estimated at 15% (of annual sale) to the distribution authority [8,9]. Moreover, according to [9], in 2017, 32.6% of firms identified the country's inadequate electricity generation to match with high load demand as a significant challenge in doing business in the country. In order to enhance the country's energy demands, several intervention approaches are being explored. Notable among these is the unbundling in 2011 of the power sector by an act of parliament into two state-owned entities, namely, the Electricity Distribution and Supply authority (EDSA) and the Electricity Generation and Transmission Company (EGTC) [10]. Both have paved the way for IPPs and other Public-Private Partnerships (PPPs) to partner with the energy market in Sierra Leone.

However, the country's energy sector remains severely challenged and requires more sustainable solutions. Modification to the Freetown load profile has long been recognized by policymakers at EDSA as an efficient technique to reduce the need for peak power generation units beneficially while meeting load demand in a planned transition to a carbon-constrained. The utilization of sustainable and reliable techniques such as the use of demand-side management (DSM) and RE injection scheme methodologies in order to meet the exponential growth in load demand of electricity in the country, is essential, especially in urban settlements. In [11], the authors evaluate various access techniques to electricity for Sierra Leoneans not connected to the grid in rural communities, and also highlighted set indicators in developing rural electrification approach and proposed the implementation of

mini-grids for rural electrification as opposed to standalone systems and expansion of the existing grid. To reduce the mismatch in the load demand and generation in the capital city of Freetown, [12] proposed optimum sizing of a ground-based energy storage system and rooftop solar photovoltaic (PV) panels for government buildings. However, the authors did not consider, implementation of DSM methodology. Moreover, [13] assessed enhancing domestic energy services for pre-urban and rural off-grid communities in Sierra Leone and analyzed various PV systems on their cost-effectiveness in achieving improved energy services. One of the primary responsibilities of IPPs is to match generation and load demand economically and sustainably. A mismatch in load demand and generation capacity will jeopardize system performance. Promotion and execution of DR programs in the capital city of Freetown are one of the most feasible solutions to meet the growth in load demand requirements for the industries and domestic consumers.

1.2. Relevant Country-Wide Reports on DSM Implementation

In recent years, researchers have given prominent attention to various strategies and methodologies towards harmonizing the mismatch in load demand and generation reliability and sustainability. Some recent studies discussed micro-grid control schemes, smart microgrids security and overhead cranes using several theoretical models [14–19]. Demand response methodologies for economically reliable operation of a smart microgrid are gaining prominence in recent times. Demand response is a potential technique applied to achieve the demand and supply balance by having the consumers rather than suppliers control the amount of power supply needed. According to [20], the contribution of DR program in the US electricity markets improved by approximately 3% to a total of 27,541 MW in 2017 compared to 2016. Furthermore, as a result of the drop in peak load demand levels in 2017, the execution of DR to matching peak load demand also increased considerably from 5.3% in 2016 to 5.6% in 2017. The author in [21] proposed DR economic model, which illustrates the change in consumption pattern of individual consumers to maximize consumer utility constrained through periodic consumption or budget. Demand-side load management methodology that is efficient in controlling residential household load at minimum cost, such that consumer satisfaction is maximized is presented in [22] also in [23], Davide Caprino et al. exemplifies an approach to the peak load shaving, management, and modelling of household appliances using real-time scheduling algorithm analysis. The scheduling method realizes a load reduction by up to 46%. DR programs have been applied in some European countries, [24–26], and execution DR have proven their potential benefits. In Norway, distinct DR programs have been executed, with the aspirations of deferring the grid capacity expansion leading to a 10% decrease in peak demand achieved for the Oslo area. After the implementation of the DR, pilot studies confirmed that the execution of the DR programs reduced the peak load by 4.5 MW, which brought about 15% energy savings for commercial consumers [27]. Reference [28] highlights the execution of interruptible load DR program in Italy for large industries that resulted in 6.5% in peak load shedding during a system emergency. H.A. Aalami et al. in [29] proposed the execution of an interruptible load DR scheme for the Iranian load curve to alter the peak load to the valley and off-peak period using price elasticity concepts. The proposed methodology will enhance independent system (ISO) to apply suitable DR program which enhances the load profile and can also be welcomed by customers.

Moreover, similar work proposed [30] for the introduction of automatic interruptible load DR scheme for residential buildings in Singapore that enhanced DR management load curtailments. In [31], the authors evaluate the economic and the technical DSM potential in Nigeria for its various industrialization strata. According to the authors, the implementation of DSM could generate 7 billion USD cumulative savings with interruptible DR programs for more significant industrial consumers. Reference [32], proposed and developed an hourly model of electricity demand for 14 countries in West Africa; from 2016–2030 and takes into account the electrification rate, occupancy patterns, household appliances, climatic condition, amongst others. Seasonal electricity demand for non-residential, electricity access rates for rural and urban was considered in the forecast model. The results show a

seasonal disparity in demand, notably higher during the dry season compared to the rainy season. Moreover, energy in West Africa is estimated to be five times in 2030 to that of 2016. Proper planning and execution of DR approaches could be a vital tool in closing the demand and supply gap. The literature in [33] reviews the electricity sector demand-side in Ghana. The author examined significant hypotheses; in essence, “the deregulation of the electricity process does not advance energy conservation.” Using the Stock and Watson dynamic, the author demonstrated that deregulating electricity prices in Ghana had influenced practices that are more harmonious with energy conservation enhancements. Moreover, in [33], simulation results demonstrated that more economic enhancement would likely jeopardize energy conservation, notably in the industrialized sector than the domestic sector. Additionally, the studies in [28,34–37] examined the significant implementation of DR scheme, RE integrations, and smart grid advanced metering infrastructure amongst others for electricity market.

1.3. Motivation for Research and Research Contribution

Power sector policymakers in several countries, especially developing countries like Sierra Leone, are faced with severe financial constraints to improve electricity access rate sustainably and reliably. Prioritizing and execution of the DR programs and incorporating RE technologies to match the constant peak load demand at a low-cost is becoming an increasingly widespread methodology, as reported in the literature. Furthermore, the implementation of DR technique for load curve levelling has been verified has a proactive approach to get energy consumers engaged in preventing detrimental power system scenarios that can jeopardize network reliability. Moreover, it could contribute to energy security and environmental sustainability while providing a secure pathway to a sustainable economy. In this research, a two-stage approach that involves the strategic combinations of several DR models, alongside the introduction of RE sources, towards modifying the customers’ demand profile is investigated for Freetown, Sierra Leone electricity market. The research objective is directed towards minimizing the disparity between the system load demand and the total available generation with minimum need for additional generation and also control the usage patterns of maximum energy demand users, which consumed the bulk of the generated power economically. The performance of the proposed model is analyzed based on the effects on the reliability and cost-effectiveness of the power system using the Freetown (Sierra Leone) distribution network. The proposed approach is an extension of the authors’ earlier work [38]; in stage-I, time-based, incentive-based, and the combination of incentive and time-based DR programs are executed using the price elasticity concept to meet the peak load demand and the modification to the load profile characteristics. Consequently, the strategic selection index (SSI) is employed to prioritize and implement relevant DR response program that is efficient from the IPPs and customer perspective and also for the most effective load profile modification. In stage II, hybridized RE technologies are included to meet the load deficit after the execution of the DR menu. Genetic Algorithm (GA) is utilized for hybridized RE infusion into the generation mix with the reduction in maintenance and operational cost as the objective function concurrently with greenhouse gas emission reduction. The overall significance of this study is to assist in implementing technical and economic evaluation to policymakers for the implementation of DSM programs and the introduction of hybrid RE technologies into the generation mix for Sierra Leone’s capital city (Freetown).

2. STAGE I: Implementation of Demand-Side Management (DSM)

DSM is a powerful energy-efficient technique that reduces or modifies the overall consumption and energy usage pattern. In the capital city Freetown, disruptions in the power supply are recurrent and leads to constant challenges to the grid and system reliability, especially during the dry season due to the considerable drop in the hydropower generation capacity. Matching the demand and supply is a massive challenge to the distribution authority. DSM is employed to reduce the mismatch in demand and supply, thereby facilitating further sustainable and less expensive funding situations. As a result of the complex characteristics of various consumers, each having their electricity usage, execution of

pertinent DSM programs is highly beneficial and can be deployed to harmonize the supply and thus enhance the grid network capacity efficiently [39]. DSM strategies such as DR enable the modification of load profiles by getting end-users to modify their consumption patterns during system constraints in order to match the generation supply. The United States Federal Energy Regulatory Commission (FERC) staff report [20] categorized DR programs regarding their operational mechanism into two broad categories (time-based and incentive-based DR programs). In the time-based program (TBP), the price of electricity in different periods are varied. Penalty or incentives are not considered for these programs. In this research, TBP considered include, Time of Use (ToU), real-time pricing (RTP), and critical peak pricing (CPP). In the incentive-based program (IBP), incentive prices are structured by the utility provider, and the customer is notified [40]. If the customers find the offered incentives prices lucrative, they will react or contrarily ignore the incentive given by the utility. IBP considered in this research include: Interruptible load (IC), load as capacity resource, direct load control (DLC), and emergency demand response (EDRP). Additional details on demand response can be found in [20,41,42].

2.1. Overview of the Proposed DSM Scheme and Analytical Modelling

Customers participating in the incentive-based DR program are required to predetermined load curtailment level when notified by the utility through advance smart metering notification whenever the system reliability is compromised. The successful execution of these programs depends on the infiltration level of the advanced smart meter system. Penalties will then be employed, for customers who failed to comply with the contractual agreement with the utility provider within a maximum annual interruption recurrence of 100 h. In this research, the IBP is considered suitable for maximum demand users (MDI). In this research, the formulation and modelling of pertinent incentive-based and time base DR programs and the impact on the Freetown load profile are outlined below. Penalties, incentives, and customer benefits are also investigated in system formulation. This research is an augmentation of earlier work presented in [38].

2.1.1. Dr Elasticity Model

According to economic principles, keeping other factors constant, a surge in energy prices will decrease its demand. Furthermore, economic principles described consumers' responsiveness to price changes as a measure of price elasticity [43]. Elasticity can be defined as the responsiveness in demand for variation in price [43,44].

$$E = \left(\frac{\partial h}{h} \right) / \left(\frac{\partial p}{p} \right) \quad (1)$$

where, E = coefficient of elasticity, p = electricity price and h = load demand.

The consumers' response to variations in the price of electricity is constrained to time considered. For instance, an increment in the price of electricity will reduce the demand in period i but may increase the demand in another period j . A negative "self-elasticity" is applied to represent the first effect and a positive "cross-elasticity" the second [45].

$$\begin{aligned} E_{ii} &= \left(\frac{\partial h}{h} \right) / \left(\frac{\partial p}{p} \right) \leq 0 \\ E_{ij} &= \left(\frac{\partial h}{h} \right) / \left(\frac{\partial p}{p} \right) \geq 0 \end{aligned} \quad (2)$$

where E_{ii} is the coefficient of self-elasticity, E_{ij} is the coefficient of cross-elasticity.

2.1.2. Modelling of Proposed Single and Multi-Period Elastic Load

Customer benefits, penalty, and incentive remuneration are crucial motivating factors for the customers to modify or curtail their initial consumption h_{0i} value to the modified demand h_i at period i , based on the predetermined contract with the utility provider [29,38].

$$\Delta h_i = h_i - h_{0i} \quad (3)$$

Incentive revenue for consumers participating in this DR program during the period i is as defined by Equation (4).

$$mn(\Delta h_i) = k_i \cdot (h_i - h_{0i}) \quad (4)$$

where the incentive rate (\$/kWh) = k_i , incentive payment (\$) = $mn(\Delta h_i)$

In a scenario whereby the participating customer fails to comply with the provision of the contract agreement, the customer must make the imposed penalty payments.

$$Z_n(\Delta h_i) = g_i \cdot (P(i) - [h_i - h_{0i}]) \quad (5)$$

where Z_n is the imposed customer penalty cost (\$), g_i is the penalty rate (\$/kWh) and $P(i)$ is DR program level of contract agreement (kWh) during the same period i . Hence, the benefit of customer C_b for period i is as shown in Equation (6) below.

$$C_b = B(h_i) - h_i \cdot p(i) + mn(\Delta h_i) - Z_n(\Delta h_i) \quad (6)$$

where $p(i)$ and $B(h_i)$ are the electricity price (\$/kWh) and customer income (\$) in i period, respectively. Assuming the customers prefer demand level h_i to maximize their benefits after the execution of DR program then, $\frac{\partial C_b}{\partial h_i} = 0$ is equated to zero thereby maximizing customer benefit.

$$\frac{\partial C_b}{\partial h_i} = \frac{\partial B(h_i)}{\partial h_i} - \rho_o(i) + \frac{\partial mn}{\partial h_i} - \frac{\partial Z_n}{\partial h_i} = 0 \quad (7)$$

So,

$$\frac{\partial B(h_i)}{\partial h_i} = p(i) + k_i + g_i \quad (8)$$

The benefit function is a quadratic function as shown below;

$$B(h_i) = B_0(i) + \rho_o(i)[h_i - h_{0i}] \left\{ 1 + \frac{h_i - h_{0i}}{2E_i \cdot h_{0i}} \right\} \quad (9)$$

where $B_0(i)$ = benefit price at nominal value, $\rho_o(i)$ = electricity prices at nominal value. Differentiating Equation (9) then solving for $\frac{\partial B}{\partial h_i}$ and substitute into Equation (8) gives;

$$\rho(i) + k_i + g_i = \rho_o(i) \left\{ 1 + \frac{h_i - h_{0i}}{E_i \cdot h_{0i}} \right\} \quad (10)$$

Customer's utilization is as expressed below;

$$h_i = h_{0i} \left\{ 1 + E_{ii} \cdot \frac{\rho(i) - \rho_o(i) + k_i + g_i}{\rho_o(i)} \right\} \quad (11)$$

From Equation (11), h_i and h_{0i} remain the same if the electricity cost prevails the equivalent without considering incentive and the penalty after the execution of the DR program.

2.1.3. Multi-Period Load Program Modelling

The cross elasticity E_{ij} , in the multi-period is calculated, for the i th period in considering all other periods applying the linearity assumption shown below [29,38];

$$\frac{\partial h_i}{\partial p_j} : \text{constant for } i, j = 1, 2, 3, 4, \dots, 24 \quad (12)$$

Moreover, a linear correlation in demand and price;

$$h_i = h_{0i} + \sum_{\substack{i=1 \\ i \neq j}}^{24} E_{ij} \cdot \frac{h_{0i}}{\rho_o(j)} \cdot \{\rho(j) - \rho_o(j)\} \text{ constant for } i, j = 1, 2, 3, 4, \dots, 24 \quad (13)$$

It follows that the multi-period including penalty and incentive model can be expressed as given below;

$$h_i = h_{0i} \left\{ 1 + \sum_{\substack{i=1 \\ i \neq j}}^{24} E_{ij} \frac{[\rho(j) - \rho_o(j) + k_j + g_j]}{\rho_o(j)} \right\} \quad (14)$$

Merging Equations (11) and (14) will result in a responsive and economic load model as shown below;

$$h_i = h_{0i} \left\{ 1 + E_{ii} \cdot \frac{\rho(i) - \rho_o(i) + k_i + g_i}{\rho_o(i)} + \sum_{\substack{i=1 \\ i \neq j}}^{24} E_{ij} \frac{[\rho(j) - \rho_o(j) + k_j + g_j]}{\rho_o(j)} \right\} \quad (15)$$

Equation (15) shows the customer maximum benefit in the 24 h period while signed to this DR program.

2.2. Demand Response Attribute Selection

Execution of DR programs enhances grid reliability. Various DR programs will have distinctive impacts on load profile attributes and market efficiency. However, it is imperative for IPPs' system operators to choose and execute related DR program, which yields an efficient market value. However, in achieving the objectives, IPP analyses different strategies such as load factor enhancement, energy consumption, peak to valley reduction, customer benefits, utility revenue, incentives, etc. On this premise, IPP prioritizes these situations by employing the Strategy Index (SI) and Strategy Success Index (SSI), as shown in the equations below [46,47].

$$SI = \sum_{i=1}^{24} \{ St_1(i)^{y_1} St_2(i)^{y_2} \dots St_m(i)^{y_m} \} \quad (16)$$

$$SI = \frac{\sum_{i=1}^z SI(i)}{\sum_{i=1}^z SI(i)(max)} \quad (17)$$

In Equation (16), $St_m(i)$ designates the performance value m th attribute for each alternative in the i th and z denotes the period under study. Equation (16), y^m depicts the weight of the m th attribute.

SSI in Equation (17), denotes the normalized value of the SI factor. The higher the SSI coefficient, the better the execution of DR programs. On this background, the IPPs prioritize distinct DR programs due to their preferences. In this research, the effectiveness of different DR programs and indices are being evaluated in Tables 1 and 2.

Table 1. Self and cross elasticity for various periods.

Period	Low Peak (00:00–7:00)	Valley (8:00–14:00)	Peak Load (15:00–22:00)
Low Peak (00:00–7:00)	−0.1	0.01	0.012
Valley (8:00–14:00)	0.01	−0.1	0.016
Peak Load (15:00–22:00)	0.012	0.016	−0.1

Table 2. Demand response programs parameters.

Program no.	Program parameters	Electricity Price US\$/kWh	Penalty US\$/kWh	Incentive US\$/kWh
0	Initial load(Base Scenario)	18.76	0	0
A	Incentive Base programs(IBP)			
1	Direct load Control (DLC)	18.76	0	22.79
2	Emergency Demand Response Program (EDRP)	18.76	0	28.49
3	Capacity Market Program (CAP)	18.76	5.8625	11.725
4	Interruptible/Curtailable (IC)	18.76	11.725	22.79
B	Time Base programs(IBP)			
5	Time of use (ToU)	7.28(Valley), 18.76(Low peak), 28.14(Peak)	0	0
6	Critical Price Peaking (CPP)	93.8 (20:00–22:00),18.76(Other hours)	0	0
7	Real Time Pricing (RTP)	7.28 (00:00–03:00),3.64 (04:00–07:00),18.76(08:00–11:00), 23.45(12:00–15:00) 18.76(16:00–18:00),58.625(19:00–21:00), 18.76(22:00–23:00)	0	0
8	ToU & CPP	7.28(Valley), 18.76(Low peak), 28.14(Peak) 93.8(20:00–22:00)Hrs	0	0
C	Incentive & Time Base programs(IBP)			
9	ToU & DLC	7.28(Valley), 18.76(Low peak), 28.14(Peak)	0	11.395
10	ToU & EDRP	7.28(Valley), 18.76(Low peak), 28.14(Peak)	0	22.79
11	ToU & CAP	7.28(Valley), 18.76(Low peak), 28.14(Peak)	5.8625	11.725
12	ToU & IC	7.28(Valley), 18.76(Low peak), 28.14(Peak)	11.395	22.79

3. Stage-Ii: Assessment of Renewable Energy (RE) Introduction

Power system resiliency centers on averting interruption in electricity supply while meeting the load demand and, in the event of an outage, restoring power supply as quickly as possible while mitigating the consequences of the outage. Network resiliency and supply reliability are of high priority for IPPs as a result of experiencing substantial financial loss due to power interruptions. The conventional approach for providing power backup during system downtime is diesel generators. However, in recent times, several RE technologies have started to gain significant roles in energy resiliency as a result of their zero-greenhouse gas emission intensity. There is an extensive backing for the use of hybridize grid-connected RE technologies, notably the solar Photovoltaic (PV) and battery energy storage systems (BESS); this provides electricity without producing any greenhouse gas emissions. RE sources have significant potential to meet current electricity demands [48]. Harnessing these to meet load demand relies on the cost and effectiveness of the technology, which is continually improving. Hence there is a continuously decreasing costs per peak kilowatt and per kWh of RE technology at the source.

In this study, the DSM approach employed when the diesel generating units in the network fails to match the required load demand after a pertinent DR program has been executed, and the RE technology has been injected. Figure 1 shows the system configuration for STAGE II analysis. Energy from the solar generators or grid power may be stored when there is a surplus generated PV power or when the cost of electricity from the grid is efficient. It is worthy to note that RE sources are being utilized in the low peak and valley periods.

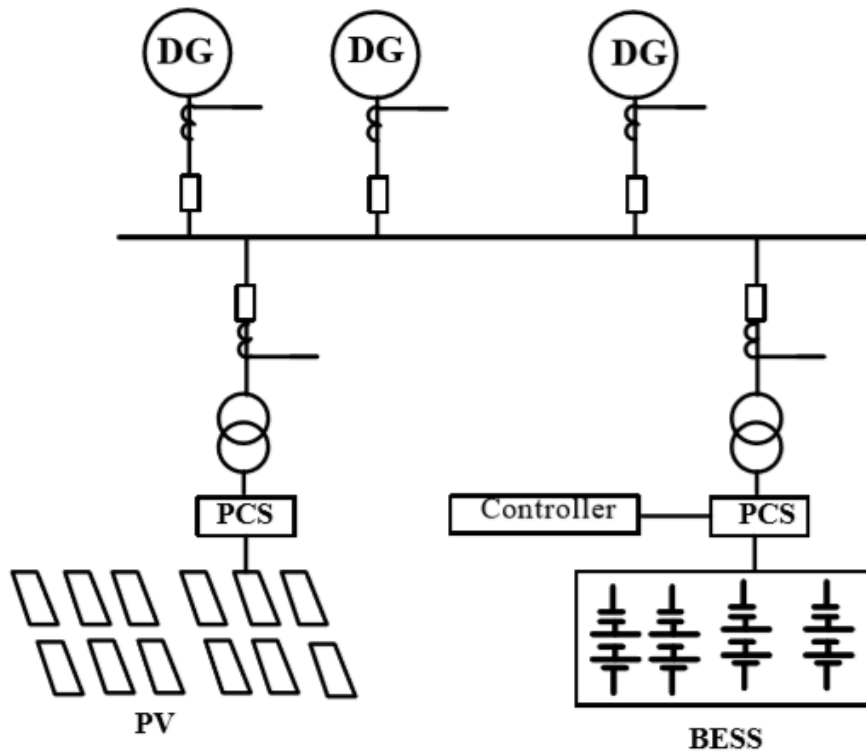


Figure 1. system configuration with renewable energy integration.

Output of Pv Array

The output power in the low peak and valley by the PV panel during period i presented as follows;

$$PV_{out} = \eta_{PV} \cdot A_{PV} \cdot R(i) \quad (18)$$

where PV_{out} depicts the output power of PV, η_{PV} = PV panels efficiency, A_{PV} = area occupied by PV panels in m^2 and $K(i)$ = solar radiation during period i in kW/m^2 .

Battery Energy Storage System (Bess) Dynamics

Thermal generating unit aggregated power P_z and that of PV panel output in period i is as follows;

$$P_x(i) = P_{pv}(i) + P_z(i) \quad (19)$$

where P_x is the summation of the generated power. From Equation (17) earlier, if the sum generated power fails to match the load demand h at a given period i , it signifies that the battery state of charge (SoC) at period i with the efficiency of the inverter η_{inv} is:

$$P_x(i) \geq \frac{h(i)}{\eta_{inv}} \quad (20)$$

At any given period, i when there is an excess generation from the thermal and PV, BESS can be charged. The state of charge is calculated as follows [38];

$$SoC(i) = SoC(i-1)(1 - \beta) + \left(P_x(i) - \frac{h(i)}{\eta_{inv}} \right) \eta_{bat} \quad (21)$$

The $SoCs(i)$, at the end of the period i , as a function of its state of charge at the preceding period of the charging or discharging that took place during the period i .

where $SoC(i)$ is the state of charge, β is the self-hourly discharge rate and η_{bat} battery charging efficiency.

$$SoC(i) \leq SoC^{max} \quad (22)$$

where SoC_{max} is 80% of the overall capacity of the battery bank. In situations wherein $P_x(i) \leq \frac{h(i)}{\eta_{inv}}$, hence there is inadequate generation capacity from, i.e., thermal and PV, the load demand will be satisfied by the BESS. Throughout the discharging period, the SoC is as shown below;

$$SOC(i) = SOC(i-1)(1-\beta) + \frac{\left(\frac{h(i)}{\eta_{inv}} - P_x\right)}{\eta_{dis}} \quad (23)$$

where η_{dis} is the battery discharge efficiency

The state of charge must be above the minimum SoC_{min}

$$SoC(i) \geq SoC_{min} \quad (24)$$

Hence the minimum state of charge is 20% of the cumulative capacity of the battery bank and in Table 3.

Table 3. Solar irradiance.

Time	Solar Radiation w/m ²	Time	Solar Radiation w/m ²
0:00	0	12:00	531
1:00	0	13:00	873
2:00	0	14:00	543
3:00	0	15:00	587
4:00	0	16:00	646
5:00	0	17:00	347
6:00	0	18:00	0
7:00	0	19:00	0
8:00	0	20:00	0
9:00	50	21:00	0
10:00	60	22:00	0
11:00	66	23:00	0

4. Case Study, Simulation Results, and Discussion

In order to assess the impact of incentive and time-based DR model, the proposed scheme is applied to Freetown load network demand for December 2017, as shown in Figure 2. The average electricity price retailed by EDSA and the Ministry of Energy (MoE) in 2018 was 18.76 USc/kWh [7,49]. The load curve is segmented in intervals depending on the nature of the demand: Low peak (00:00–7:00), valley (8:00–14:00), and peak load (15:00–22:00).

4.1. Stage I: Implementation of DSM

DR program is executed to decrease the demand in peak load periods. Data was obtained through key informant interviews, sector policymakers, desk research, discussion with senior engineers at EGTC and EDSA. In this research, the implementation of the proposed scheme during system contingency is a 10% modification of the total load of the participating customer. Moreover, incentive and time-based DR programs are analyzed in this study. The incentive-based programs (group A) comprise; DLC, EDRP, CAP, and IC. Time-based programs (group B) comprise; ToU, CPP, RTP, and combination of ToU and CPP. Furthermore, in group C, the combination of incentive and time base programs are investigated. The price elasticity designated for customers who signed up for this program and incentive and penalty values are shown in Tables 1 [38] and 2, respectively. Table 2

data was formulated by authors through key interviews of policymakers at EDSA, EGTC, Ministry of Energy, and the customers.

1. Initial load (base case): The peak load curve considered without the implementation of the proposed DR program in Figure 2 as shown in Table 5 and Figure 3, the peak load is 96.5 MW, the energy consumption of 2085.7 MWh, a load factor of 87%, which depicts the lowest after the execution of the proposed scheme with a maximum peak to valley reduction of 22.500 MW observed. These four indices improved after implementation of the proposed DR model, as subsequently illustrated in the following subsections. Moreover, in Table 4, customer bill and utility revenue of \$377,050 are achieved concurrently.
2. Program 1: In this case, the DLC program is implemented. From Table 2, the incentive and penalty are given as 22.79 Us/kWh and 0 Us/kWh, respectively. In this program, IPPs reward consumers for modification in their load profile with zero penalties for load curtailment failure. From Tables 4 and 5 and comparing the results to the baseload; peak reduction of 90.73 MW (5.98% peak reduction) is achieved. Moreover, as shown in Figure 3, the load profile characteristics enhanced the customer's benefit to \$42,052 with a peak to valley and energy reduction by 25.6% (16.73 MW) and 3.37%, respectively.
3. Program 2: In this case, EDPR is executed, from Table 2 with incentive value of 22.79 Usc/kWh for load modification, with 0 Usc/kWh as the penalty, which implies that IPPs do not penalize customers for the violation if customers fail to modify the load agreed in the contract level. From the simulation results shown in Tables 4 and 5, peak load reduction of 94.70 MW (1.86%), energy reduction of 0.50%, peak to valley reduction of 20.70 MW (8%), customer benefit of \$3835 attained relative to the base case.
4. Program 3: In this program, CAP is implemented, and it assumed that 11.725 Usc/kWh is the penalty fee if customers fail to modify their load profile to a predetermined level during system contingency, and 5.8625 Usc/kWh as incentive fee for load profile alteration is employed by the IPPs. The result of executing this program is as shown in Figure 3. From the simulation results, shown in Tables 4 and 5, 2066.60 MWh reduction in energy consumption, 0.92 % of energy reduction, 19.21 MW (14.6%) peak to valley reduction is observed as compared to the base case. Moreover, the load factor of 92 % and customer benefit of \$6316 achieved.
5. Program 4: For this program, the IC program is implemented, as shown in Figure 3. The penalty and incentive values set as 11.725 Usc/kWh and 22.79 Usc/kWh, respectively. Enhancement in the load profile characteristic with customer benefit of \$51,303, is shown in Table 4. Furthermore, 91.62 MW (5.06%) of peak load reduction, 5.19% energy reduction, and 17.620 MW (21.69%) peak to valley reduction were achieved as compared to the base case shown in Table 5 with an achieved load factor increment of 90%.
6. Program 5: As shown in Tables 4 and 5 and Figure 4, the ToU program is implemented, with a reduction of 91.18 MW (5.51%) peak load, 0.48% energy reduction, 2075.6 MWh energy consumption, peak-to-valley by 17.18 MW (23.65%) as compared to the base case. Moreover, the customer benefit of \$8835 was achieved.
7. Program 6: In this case, the CPP program implemented at 19, 20, and 21 h, respectively, as shown in Table 2. The results obtained after the execution of the program in Tables 4 and 5, Figure 4, shows enhancement in the load profile with customer benefits of \$ 25419. This program has the highest customers' bills, and a peak load reduction of 2.09%, in correlation with other programs due to the high electricity price. Moreover, an increase in energy reduction to 0.03% is observed.
8. Program 7: As shown in Figure 4, the load profile characteristic is enhanced after the implementation of the RTP program. As shown in Tables 4 and 5, the peak reduction of 93.02 MW (3.61%) and peak to valley reduction of 18.764 MW (16.6%) is realised in correlation with the base case. Moreover, there is an upsurge in the energy reduction of 0.17% and the load factor of 94%, which is the second-highest after the execution of the program as compared with the base case, with customer benefit of \$11,079.

9. Program 8: In this program, the ToU and CPP are executed concurrently, as shown in Figure 4. From the simulation result shown in Tables 4 and 5, a load factor of 94% and 19.53 MW (13.12%) peak to valley reduction achieved, which is the maximum. Moreover, the customer benefit increased to \$27,460, and the energy consumption reduced by 2102.3 MWh (0.8%) in assessment with the base case.
10. Program 9: In this program, ToU and DLC are executed concurrently, as shown in Figure 5 with enhanced load profile characteristics. From the simulation results shown in Tables 4 and 5, 90.20 MW (6.54%) peak load reduction, 16.20 MW reduction in peak to valley, 2.16% in energy reduction in comparison with the base case. Moreover, 94% load factor, which is the highest after the execution of this program and customer benefit of \$29,409, was attained.
11. Program 10: In this program, ToU and EDRP are executed concurrently, enhancement in the load profile characteristics is obtained, as shown in Figure 5. Moreover, an increase in the customer benefit of \$60,025, peak load reduction, and peak to valley load reduction is accomplished, as shown in Tables 4 and 5.
12. Program 11: In this program, ToU and CAP executed simultaneously. As shown in Figure 5, the attributes of the load profiles are enhanced. As shown in Tables 4 and 5, a peak load reduction of 90.67 MW (6.05%), reduction in energy consumption by 3.09% (2023.20 MWh), peak to valley reduction by 16.166 MW (28.1%) was achieved, while customer's benefit increased by \$29,901 was attained in comparison with the base case.
13. Program 12: The ToU with IC executed concurrently. The load attribute of the load profile improved. From the simulation results shown in Tables 4 and 5, 4.74% (91.93 MW) peak load reduction, energy reduction by 5.68%, and peak load to valley reduction of 0.3 % (22.45 MW) in comparison with the base case. Moreover, this increased customer benefit to \$70,048, which is the maximum in the execution of this program was achieved.

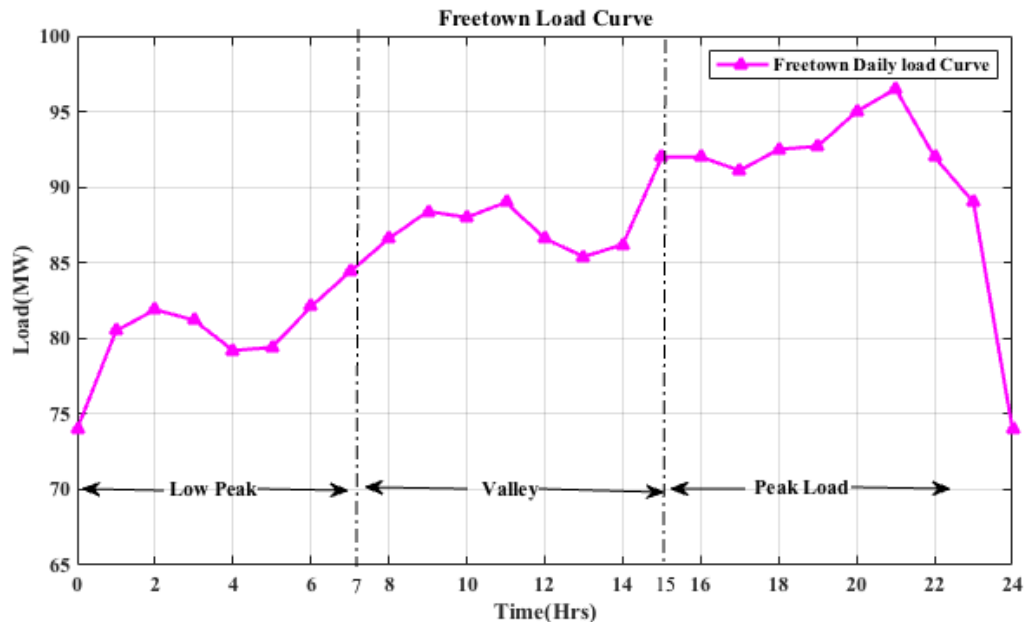


Figure 2. Freetown demand curve.

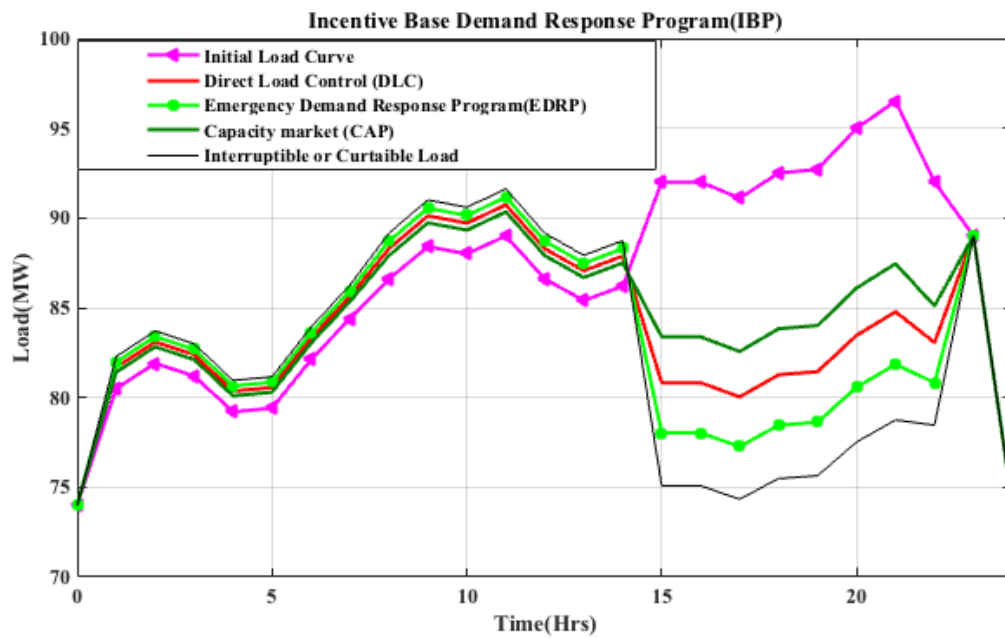


Figure 3. Impact of incentive base program.

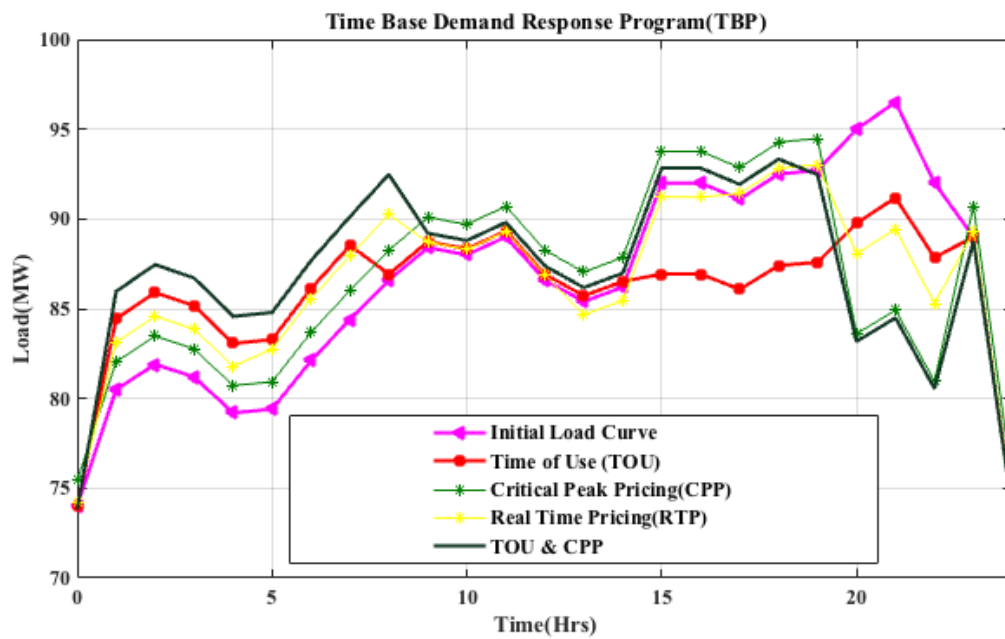


Figure 4. Impact of time base program.

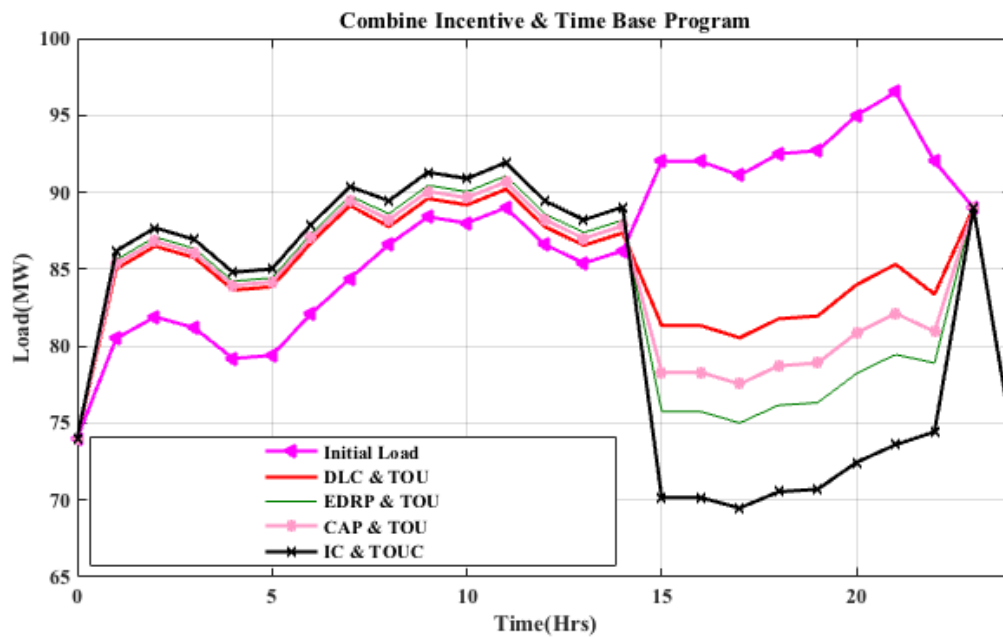


Figure 5. Impact of time and incentive base program.

Table 4. Economic analysis of demand response profile.

Program No.	Program Parameters	Incentive (\$)	Penalty \$	Customer Bill (\$)	Customer Benefit (\$)	Utility Revenue (\$)
0	Initial load(Base Scenario)	0	0	377,050	0	377,050
1	DLC	20,083	0	355,080	42052	334,990
2	EDRP	471	0	373,680	3835	373,210
3	CAP	1414	1256	37,090	6316	370,730
4	IC	30,416	12,385	343,770	51,303	325,740
5	ToU	0	0	368,210	8835	368,210
6	CPP	0	0	578,600	25,419	578,600
7	RTP	0	0	422,560	11,079	422,560
8	ToU & CPP	0	0	535,730	27,460	535,730
9	ToU & DLC	9589	0	357,230	29,409	347,640
10	ToU & EDRP	29,220	0	346,240	60,025	317,020
11	ToU & CAP	12,675	8563	351,260	29,901	347,150
12	ToU & IC	39,262	11,003	335,260	70,048	307,000

Table 5. Technical analysis of demand response load profiles.

Program No.	Program Parameters	Peak (MW)	Peak Reduction (%)	Energy Consumption (MWh)	Energy Reduction (%)	Load Factor (%)	Peak to Valley (MW)
0	Base Scenario	96.50	0.00	2085.70	0.00	87	22.50
1	DLC	90.73	5.98	2017.70	3.37	93	16.73
2	EDRP	94.70	1.86	2075.30	0.50	91	20.70
3	CAP	93.21	3.40	2066.60	0.92	92	19.21
4	IC	91.62	5.06	1982.80	5.19	90	17.62
5	TOU	91.18	5.51	2075.60	0.48	95	17.18
6	CPP	94.48	2.09	2086.30	−0.03	92	19.06
7	RTP	93.02	3.61	2089.20	−0.17	94	18.76
8	ToU&CPP	93.34	3.28	2102.30	−0.79	94	19.53
9	ToU&DLC	90.20	6.53	2041.70	2.16	94	16.20
10	ToU&EDRP	91.06	5.64	2007.70	3.89	92	17.06
11	ToU&CAP	90.67	6.05	2023.20	3.09	93	16.67
12	ToU&IC	91.93	4.74	1973.70	5.68	89	22.45

4.2. Prioritizing DR Program for IPPs and Customer Perspective Using SSI Analysis

In this study the strategic selection index, as shown in Equations (16) and (17) are used to prioritize and select appropriate DR programs, as shown in Table 6 and Figures 6–8 from the IPPs and customer perspective. In addition to the revenue, the load factor has significant relevance to the IPPs evaluation, while the customer benefit is an essential motivating factor to the customer, as shown in Table 6.

Usually, when constraints exist for execution of a specific program with higher demand, the IPPs can select distinct programs with a cost-effective requirement.

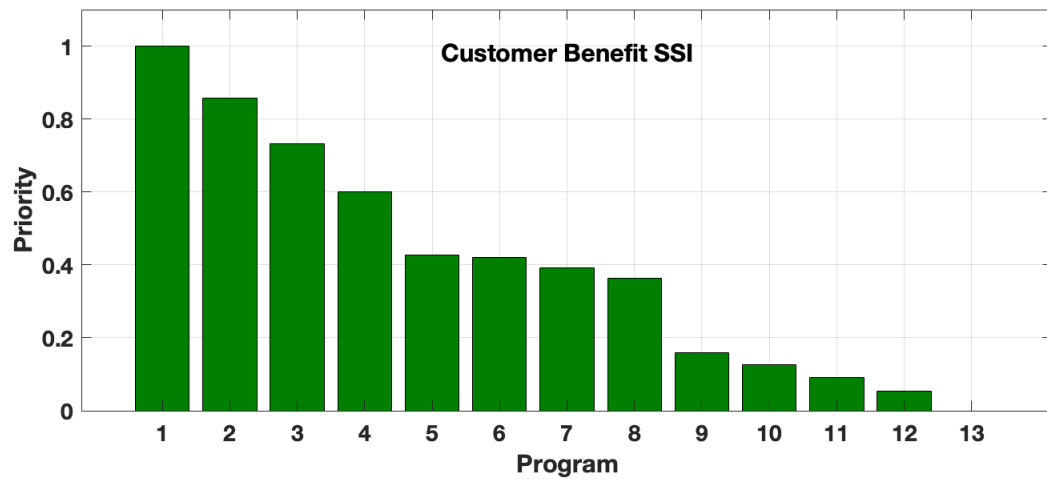


Figure 6. Customer benefit strategic selection index (SSI).

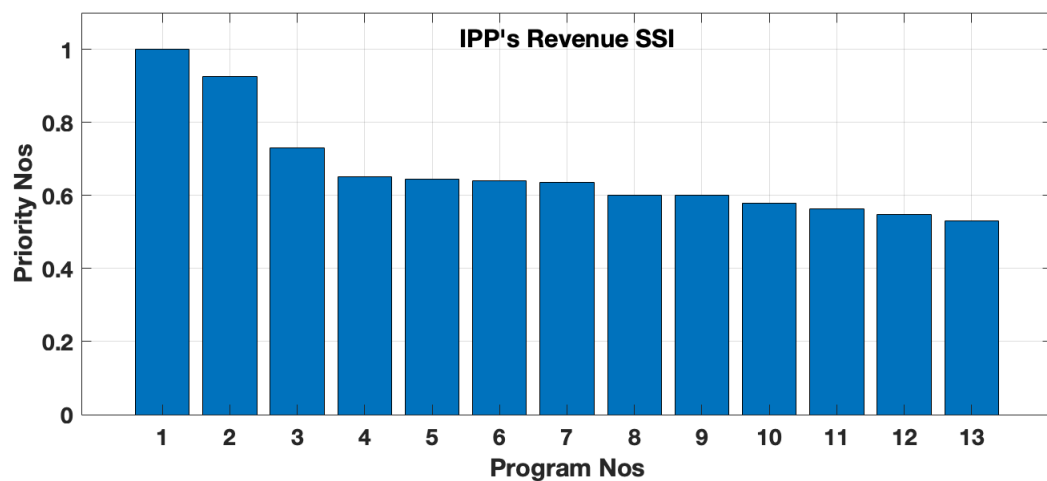


Figure 7. IPP revenue SSI.

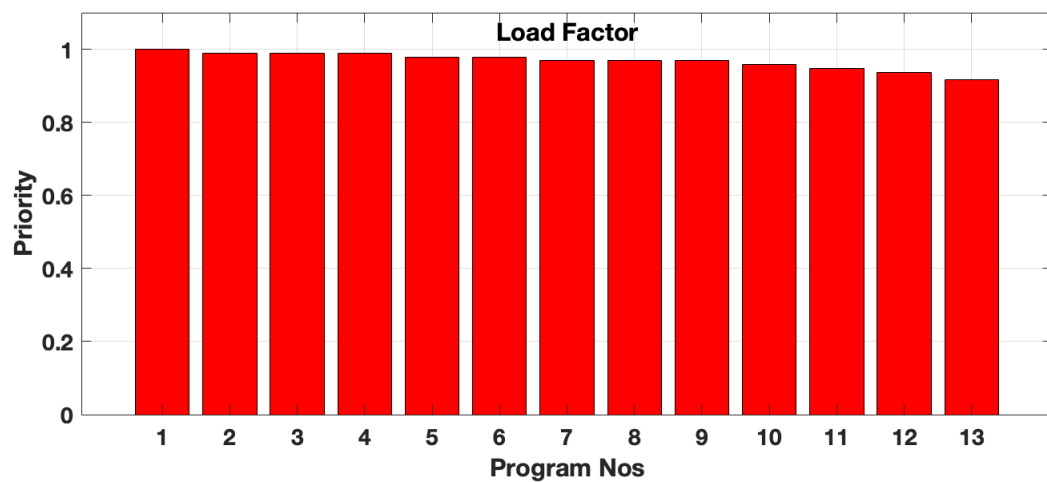


Figure 8. Load factor SSI.

Table 6. Prioritizing demand response (DR) programs using strategic selection index.

Program Priority Order	CUSTOMER BENEFIT		IPPs REVENUE		LOAD FACTOR	
	Demand Response Program	SSI%	Demand Response Program	SSI%	Demand Response Program	SSI%
1	ToU&IC	100.00	CPP	100.00	ToU	100.00
2	IC	73.24	ToU&CPP	92.59	ToU & DLC	99.44
3	ToU&EDRP	64.45	RTP	73.03	ToU & CPP	98.95
4	EDRP	54.36	BASE CASE	65.17	CAP	98.87
5	ToU&CAP	48.14	ToU	63.64	RTP	98.67
6	ToU&CPP	39.22	CAP	62.72	ToU & CAP	98.03
7	DLC	36.50	ToU&DLC	61.67	DLC	97.69
8	CPP	36.29	DLC	60.75	CPP	97.01
9	ToU&DLC	28.91	ToU&CAP	59.33	ToU & EDRP	96.86
10	CAP	20.20	EDRP	58.58	EDRP	96.42
11	RTP	15.82	ToU&EDRP	57.36	IC	95.07
12	ToU	12.61	IC	56.30	ToU & IC	94.32
13	BASE CASE	0.00	ToU&IC	53.06	BASE CASE	91.43

Table 6 shows the highest priority attained by simultaneous execution of time-based and incentive-based DR programs for both the IPPs' and customers' point of view. Evaluating the performance value of the different scenarios considering the customer benefits, IPPs revenue, and the load factor, using the SSI coefficient is considered to be 100% for the most effective program, as shown in Table 6 and Figures 6–8. From the analysis shown in Table 6, the ToU/IC, CPP, and ToU proved to be most effective from the customer and IPPs' perspective considering customer bills, IPPs revenue, and load factor, respectively.

Stage II: Introduction of Renewable Energy

Figure 9 exhibits the injection of RE technologies in the generation mix after the implementation of the DR scheme. The proposed model is assessed by utilizing a Genetic Algorithm (GA). GA is an approach to solve both unconstrained and constrained optimization problems based on natural selection. A key stage in GA applications is the definition of the objective (fitness) function, which is the function to enhance. In this instance, the fitness functions are the summation of the net disparity between the load and the generation, i.e., for peak load, valley, and low peak periods. Equation (25) below shows the fitness function (F_{nx}).

$$F_{nx} = \min \sum_{i=1}^N | \{gen - load\} | \quad (25)$$

In this study, BESS and PV are injected to compensate for the mismatch in the present generation capacity from the thermal units primarily during peak and valley periods prominently throughout the dry season, when the main hydropower supply to the capital city decreased to more than its designed capacity due to climatic conditions. Table 3 shows the solar irradiance [50]. The synchronized execution of ToU and IC selected for the penetration of BESS and PV due to its load factor index is shown in Table 6 after the execution of DR. It represents the lowest load factor index. Moreover, an extensive mismatch in the load profile characteristic is observed and should be covered in the valley and peak interval. From the simulation results shown in Figure 9, within the hours 00:00–10:00 where we have inadequate solar radiation, the BESS can be seen discharging its stored energy covering the deficiency for the PV power. From 11:00–14:00, we observed an increase in solar irradiance. During this period, the PV will be providing power supply while the BESS is charging as we reach the peak load period. The state of discharge and charging is, as shown in Figure 9.

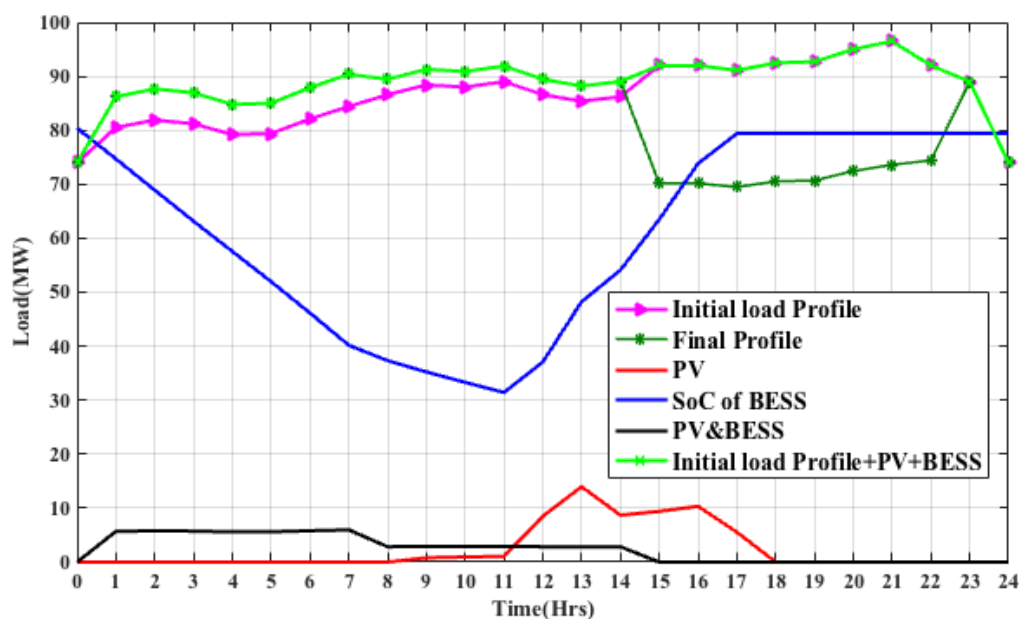


Figure 9. Renewable energy injection.

5. Conclusions

In this research, a two-stage DR program-curtailed optimal integration of hybridized RE source has been implemented to meet the daily load demand for Freetown, Sierra Leone. In Stage-I, time-based, incentive-based, and the combination of incentive and time-based DR programs are executed using the price elasticity concept to meet the peak load demand. From the simulation results analysis, for CAP and the simultaneous execution of ToU with DLC 6.5% and 6.39 % peak load reduction are attained, respectively. Both yielded the highest benefits of the executed proposed DR programs scheme; The reduction of energy consumption of 2041.7 MWh was achieved with CAP and 2033.2 MWh as achieved with ToU-DLC. Both scenarios enhance peak load reduction with significant modifications to the customers' load characteristics. The SSI analysis is employed to prioritize and implement relevant DR response programs that are efficient from both the IPPs' and customers' perspective. From the results obtained, the CPP and concurrent execution of ToU and IC DR programs prove to be economically efficient from the IPPs and customer perspective. Moreover, considering the load factor based on the SSI analysis, the ToU program is found to be more productive. Conclusively, Stage II of this study involved the optimal introduction of hybridized RE technologies to satisfy the new load profile after the execution of the relevant DR programs. Genetic Algorithm (GA) was utilized for the optimal RE infusion into the generation mix with the reduction in maintenance and operational cost as the objective function, alongside greenhouse gas emissions reduction. The results show the ability of the proposed control scheme to match the increased load demand in off-peak and valley periods that shifted from peak periods due to utilizing the DR approach. In the future, the research will be extended towards investigating the possibilities of a very high renewable energy fraction using appropriate demand-side management approach and generation extension planning.

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